Estimating Labor Supply at the Extensive Margin in the presence of Sample Selection Bias

Marko Ledic

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Abstract

This paper illustrates the static labor supply model using a large cross sectional data set encompassing the countries of Great Britain. I focus on estimating the labor force participation decision what is referred in the literature as labor supply on the extensive margin. The sensitivity along the extensive margin is expressed by calculating two specifications of a participation elasticity, defined as the percentage change in the labor force participation rate induced by a one percentage change in the gross wage or the net effective wage. The elasticities of labor supply are computed separately for men and women. The basic problem in estimating labor supply models with non-workers is unobservability of their wage rates that makes a non-random nature of the sample. I follow Heckman (1979) approach to correct for sample selection bias by estimating wage equation for workers and non-workers. Predicted wage rates along with non-wage incomes and a range of household characteristics are used in the probit regression model while the standard errors of the predicted wage rates were bootstrapped to correct for error-prone sampling distribution of predicted wage regressors that are non-linear functions of the estimated model parameters. I find that semi-elasticities of labor supply on the extensive margin with respect to gross wage are 0.09 and -0.03 percentage points for men and women, respectively. Using the net effective wage rate these elasticities are 0.10 and -0.01 for men and women, respectively. Both estimated elasticities are marginally larger in the net effective wage specification which I interpreted as a marginal incentive for men to join the labor market and less disincentive effect for women to withdraw from the labor market.

JEL Classification: D12, D31, H20, J22
Keywords: Labor supply, wage elasticity and sample selection

Contents

1 Introduction

The literature on labor supply occupied for several decades a crutial theoretical and empirical role in economic research. The main reason for a great concern for this topic has to do with knowing the responses of labor supply to after tax wages and transfers in order to construct the effective welfare system. As Keane (2011) pointed out, it is logical that much the labor supply literature concerns on how income taxes affects peoples' incentives about working hours. However, the literature on labor supply is characterized by very distinct conclusions about the size of labor supply elasticities and methodological procedures that were used. Most studies have found small labor supply elasticities for men but large labor supply elasticities for women, with respect to after tax wage rates. Kosters (1969) was the first to estimate labor supply function for employed married men, obtaining a negative Marshallian elasticities on wage and non-labor income but many problems in estimation were ignored. Ashenfelter and Heckman (1973) followed by Masters and Gartfinkel (1977) estimated small and negative Marshallian elasticities for married men accounting for the measurement error that arrises from endogeneity in wage or non-labor income. The British studies of male labor supply begin with Brown, Levin and Ulph (1976) who estimated wage elasticty of hour of work of between -0.085 and -0.131 at sample mean values. Using picewise linear budget constraint to find the optimal number of working hours, Ashworth and Ulph (1981) computed negative wage elasticity of hours of work of between -0.07 and -0.13. Layard (1978) estimates uncompensated wage elasticity of -0.13 using a sample of married men.

The literature on labor supply for women focused on modeling the participation due to the large extent of non-participation among women[1]. For women, uncompensated elasticity of hours of work with respect to wage is estimated by Dooley (1982), Nakamura and Nakamura (1981), and Nakamura, Nakamura and Cullen (1979). In all these studies they calculated labor supply elasticity with respect to wage of -0.30 or less. Dooley (1982) and Heckman (1980) computed labor supply elasticity with respect to wage in excess of 14.00. Smith and Stelcner (1985) calculated small and positive labor supply elastity with respect to wage. The reason for large variation in uncompensated wage elasticity for women is because the procedures employed in these studies differ substantially. Important contribution to female labor supply elasticity comes from Mroz (1987) who conducted sensitivity analyses and obtained wage elasticity from -0.02 to 0.09. The impact of tax reforms on labor supply were to be of a great concern for empirical applications. Eissa and Liebman (1996) estimated the effects of Tay Reform Act and Earned Income Tax Credit on labor supply for single women and then they compared the change in labor supply for women with children to the change in labor suppyl for women without children. The results showed an increase in the participation of women with children by 1.9-2.8 percentage points relative to women without children. Blundell et al. (1998) focused on tax reforms in the UK over the 1980s and early 1990s to find labor supply effects of

[1] For modeling the participation decision, see Heckman (1974).

married women from a series of repeated cross-sections. They computed small and positive unompensated labor supply elasticities while the income elasticities were negative, except for those women without children. Eissa et al. (2004) studied the labor supply and welfare effects for single mothers in the US following for tax acts, incorporating both the intensive and the extensive margin of labor supply. Their findings were that the welfare gains are generated by the participation responses of single mothers.

Numerous tax and benefits reforms, like the Family Credit system or the Working Families Tax Credit in the UK and the Earned Income Tax Credit on the US, are created in order to induce a greater labor force participation rates. However, sometimes increasing the generocity of benefit systems might produce unintendent effects of making employment relatively less attractive that in the first time before this change. Dilnot and Duncan (1992) created negative employment responses that were incentivized by the UK's Family Credit system. Thus, modelling labor supply responces to changes in tax-benefit systems are necessary for understanding the welfare effects of these changes. Specifying the functional form for capturing labor supply effects in behavioural microsimulation occupies an important place in empirical work. In continuous estimation approach it is favoured to derive the direct or inderect utility function from the maximization problem, see Arrufat and Zabalaza (1986) and Hausman (1981). Another option that is the most suitable for estimating discrete models is to assume a form of direct utility function.

Some of modelling difficulties for empirical work of labor supply includes the enodgeneity and heterogeneity problems, inclusion of stochastic elements in microsimulation and dealing with nonlinear nature of tax-benefit systems. These difficulties are tempted to resolve by using continuous or discrete approach in estimation. In order to deal with difficulties of the tax schedule, Hall (1973) linearized the budget constraint around observed working hours. However, Burtless and Hausman (1978) showed that presece of measurement error in the level of hours implies biased estimation of parameters in the model. They developed a descripton of the budget constraint that serves as an alternative to constructing the marginal tax rate. The following model is then estimated in work by Arrufat and Zabalaza (1986), Hausman (1981, 1986) where the optimal number of working hours is determined by comparing the utility defined over each linear segment of the budget constraint with the utility obtaied when not working. Blundell, Duncan and Meghir (1992) estimate a labor supply model while including a selection correction term to correct for selection bias. Estimation of the labor supply responses of married women while correcting for selection bias is done by Blundell, Duncan and Meghir (1998). There exists a numerous studies that estimated labor supply models incorporating discrete budget set, see for example Blundell, Duncan , McCrae and Meghir (1999), Callan and Van Soest (1996), Keane and Moffitt (1988), Van Soest (1995).

Another problem that arrises in estimation of a labor suppy models is concerned with the unobservability of wage rates for non-working individuals. The solution has been found in estimating the expected market wages that can be used in place of missing data for non-working individuals. Heckman (1979) developed a method that estimates conditional expectation on wage rates controlling for sample selection. Modelling non-participation is often very important issue when assessing the effects of tax and benefits reforms on labor supply. Very often studies that deal with the impact of taxes and benefits on labor supply are assuming that reservation wages exceed the market wages for participants. Mroz (1987) pointed out, that simply assuming corner solution for non-participants creates an econometric problems in estimation. Another aspect in estimation that affects the likelihood that a pontential worker becomes employed and can be controlled for are fixed costs of employment, see for example Blundell, Ham and Meghir (1987) and Cogan (1981).

There is the distinction between decision whether to work at all and how much working hours to supply at the individual level. The former is reffered as the extensive margin of labor supply, calculated as the number of individuals that were employed and the latter is reffered as the intensive margin of labor supply, calculated as thr number of hours worked. In microeconometric studies the size of wage elasticities at these two margins showed different results with respect to some demographic characteristics (Blundell & Macurdy (1999)). Empirical evidence confirms that the elasticity at the extensive margin is larger than the elasticity at the intensive margin, which means that individuals tend to react more sensitively at participation decision than on the supply of average working hours. However, this does not imply that the decisons on the extensive margin accounts for a larger welfare gains. Blau and Kahn (2007) argues that the labor supply elasticities of men and women equated recently due to incresed labor force participation of women. The distinction between the extensive and intensive margins is based on the time span for which these changes are accounted for. For example, numerous microeconometric studies concentrated on weekly hours of work what is in contrast with some other studies that are using annual hours of work.

This thesis estimates labor supply responses in Great Britain, using the general household survey for the year 2005. I follow Heckman (1979) to estimate a wage equation controlling for the selection bias into employment. After predicting the wages for everybody in the sample I estimate the wage labor supply elasticity at the extensive margin using the gross wage and the net effective wage, which is constructed by taking into accout paid taxes and received benefits. The difference between the two wage specifications designates the effect of tax-benefit system on the labor supply which intuitively characterises the welfare system. The effects of demographic variables on the labor force participation are presented subequently. Section 2 introduces the theoretical framework of static labor supply. Section 3 presents the econometric framework of Hackman sample selection model and the participation decision model. Section 4 presents a detail description of dataset used in estimation. Section 5 presents results on elasticities at extensive margin and effects of demographic variables on labor frce participation. Section 6 concludes.

2 The static model of labor supply

The basic setup for a static labor supply problem consists of an individual or a household containing a single worker faced with the choice of the optimal amount of time an individual would like to work and the choice of choosing the optimal amount of consumption bundles. The direct approach to finding the agent's labor supply function is to maximize strictly increasing, strictly quasi-concave utility function subject to given constraints. The indirect utility function can be expressed as:

$$V(p, w, y) = \max_{c,h} U(c, H - h) \tag{1}$$

The utility maximization problem is subject to the following constraints:

$$c \leq wh - T(wh, y, Z) + y, \tag{2}$$

$$H \geq H - h \geq 0, \tag{3}$$

$$c \geq 0 \tag{4}$$

where $U(\cdot)$ is a well defined utility function which is strictly increasing in consumption c and leisure $l = H - h$, that is comparable to other goods. Hours of work are denoted by h, the agent has non-labor income and other household income denoted by y. Beside that, the agent is endowed with labor income wh, where productivity or hourly wage rate is denoted by w. The tax system is defined as the amount of paid taxes minus received transfers to public sector and it is described by a function $T(wh, y, Z)$. Net payment to public sector, $T(wh, y, Z)$, depends on the level of individual's labor and other household income and demographic characteristics of the household Z. The second constraint means that a negative amount of working time cannot be supplied and that labor supply is not feasible above the time endowment H. In addition, a negative amount of goods cannot be consumed. For simplicity, I assume that there is only a single consumtion good, where the price of consumption good is taken as the numeraire.

One can divide and solve the following problem in two phases. First phase is to solve for the optimal hours of work controlling for the employment decision and in the second phase the agents' are choosing whether to participate or not in the market at the optimal working hours. Solving for the first phase by setting up the Lagrangean and assuming that an interior optimum with respect to consumption decision and hours of work holds[2]:

$$L(c, h, \lambda; p, w, y, T) = \max_{c,h} U(c, H - h) + \lambda(wh - T(wh, y, Z) + y - c) \tag{5}$$

[2] In other words, this assumption implies that the last two constraints are non-binding.

The first order conditions at the interior optimum after equating them with zero are:

$$L_c = \frac{\partial U(c, H-h)}{\partial c} - \lambda = 0 \tag{6}$$

$$L_h = -\frac{\partial U(c, H-h)}{\partial h} - \lambda \left[w - \frac{\partial T(wh, y, Z)}{\partial (wh)} w \right] = 0 \tag{7}$$

$$L_\lambda = wh - T(wh, y, Z) + y - c = 0 \tag{8}$$

The first two conditions can be rewritten as:

$$-\frac{\partial U(c, H-h)}{\partial h} = (1-\tau_i) w \frac{\partial U(c, H-h)}{\partial c} \tag{9}$$

where $\tau_i = \partial T(wh, y, Z)/\partial(wh)$ is the marginal tax rate of working an additional hour which includes the marginal tax rate and the reduction in transfers due to increased the individual's earnings. The solution to the maximization problem above is represented by the Marshallian demand functions:

$$c^0 = c(p, w, y, Z) > 0 \tag{10}$$

$$h^0 = h(p, w, y, Z) > 0 \tag{11}$$

$$l^0 = H - h^0 = l(p, w, y, Z) < H \tag{12}$$

$$\lambda^0 = \lambda(p, w, y, Z) \tag{13}$$

In the second phase, the solution is found for the participation decision. If the utility from participation is greater then the utility that is obtained when non-participating, $U(c^0, h^0) \geq U(c_0, 0)$, an individual decides to enter the labor market. For those individuals who are not participating in the market, the optimal consumption c_0 contains the transfers from public sector for unemployment, non-labor income and other household income, $c_0 = -T(0, y, Z) + y$. For individuals that participate in the labor market, they have optimal consumption c^0 that is sum of individual's labor income, non-labor income, other household income minus net payments from the public sector:

$$\begin{aligned} c^0 &= wh^0 - T(wh^0, y, Z) + y \\ &= wh^0 - T(wh^0, y, Z) + c_0 + T(0, y, Z) \\ &= c_0 + wh^0 \left[1 - \frac{T(wh^0, y, Z) - T(0, y, Z)}{wh^0} \right] \\ &= c_0 + (1-\tau) wh^0 \end{aligned} \tag{14}$$

where $\tau = \left[T(wh^0, y, Z) - T(0, y, Z) \right] / wh^0$, denotes the effective marginal tax rate on the labor force participation. The solution for the optimal number of hours of work h^{0*} is the following:

$$h^{0*} = \begin{cases} h^0 & \text{if } U(c^0, h^0) \geq U(c_0, 0) \\ 0 & \text{if } U(c^0, h^0) < U(c_0, 0). \end{cases} \tag{15}$$

The labor supply decision of an individual is represented in two separatate choices. The first choice for an individual is to choose whether or not to participate in the market, that is the labor supply at the extensive margin. The second choice is to choose the optimal number of hours of work conditional on the participation, what is denoted as the decision on the intensive margin. In estimating the labor force participation behavior I am following the extensive margin approach. Rationale behind that, among the others, is implied in the nature of labor contracts that are not flexible enough to allow workers to choose desired number of hours of work. Moreover, for different occupations where the workers choose wage levels and hours of work, simultaneous estimation of labor supply is needed.

3 The econometric model specification

In this section I illustrate the econometric theoretical framework to analyze labor supply at the extensive margin when unobserved characteristics influence the level of the market wage to non-working individuals in the sample. This presents a problem in estimating behavioral labor supply responses since the wage rate for non-workers is not observed. I begin with the specification of the Heckit model that enables to factor unobserved characteristics by estimating the expected market wage for the non-working individuals. Then, I describe the participation probit model which is employed as the basic econometric framework for the empirical analysis of labor supply.

3.1 Heckman sample selection model

The OLS estimation in selected samples leads to inconsistent parameter estimation even if population conditional mean is linear in right hand side variables. To obtain consistent estimation of the parameters of interest, alternative estimation techniques that rely on stronger distributional assumptions are therefore necessary. Here I present the Heckman (1979) bivariate sample selection model that is used in the first part of the estimation. The bivariate sample selection model generalizes the Tobit (1958) model with the specification of a censored latent variable that is used as the indicator for the another latent variable that determines the outcome of interest[3]. It is important to notice that a selected sample is a synonym for a nonrandom sample that results either from sample design or from nonresponsive behavior of respondents on questions in the survey.

The Heckman model introduces a latent variable y_1^* and the outcome latent variable y_2^*. In the labor supply terminology, y_1^* denotes the unobserved propensity to work and y_2^* denotes the supply of working hours. The problematic part of the labour supply estimation lies in the fact that a main determinant, wage, is not observed for non-working individuals. If people make their decisions about employment randomly, we could then ignore the fact that not all wages are observed and OLS estimation remains appropriate technique for estimating the participation decisions. Nonetheless, it does not seem plausible to belive that people randomly decide about the supply of their working hours. Individuals who would have high wages may decide to the participate in paid labor market with higher probability than the others with lower wages. Therefore, the estimated parameter on wage is upwardly biased when it is estimated without taking into account a sample selection effect. One of the approach to tackle this problem is given by Mroz (1987), who introduces a wage equation and substitutes it for first latent variable equation. Then one can find the variable affecting the selection to work but not the wage offer equation. The participation equation can be defined as:

[3] Amemiya (1985) termed this model as the Tobit type II, while Wooldridge (2002) called it a probit selection equation.

$$y_1 = \begin{cases} 1 \text{ if } y_1^* > 0 \\ 0 \text{ if } y_1^* \leq 0 \end{cases} \tag{16}$$

The outcome equation is given by the following expression:

$$y_2 = \begin{cases} y_2^* \text{ if } y_1^* > 0 \\ \cdot \quad \text{ if } y_1^* \leq 0 \end{cases} \tag{17}$$

What follows from the two equations system is that whenever y_1^* is positive then y_2 will be known, whereas for non positive y_1^* we can not observe y_2. One misleading approach that can lead to inappropriate use of the Heckman model will be to set y_1 to zero when $y_2 = 0$. However, there is no justification to set the offered wage rate to zero just becuase it is not observed. Further, the Heckman sample selection model assumes the linearity in regressors and additive error terms of the two equations system:

$$\begin{aligned} y_1^* &= \mathbf{X}_1'\boldsymbol{\beta}_1 + \xi_1 \\ y_2^* &= \mathbf{X}_2'\boldsymbol{\beta}_2 + \xi_2 \end{aligned} \tag{18}$$

where $\mathbf{X}_1$and $\mathbf{X}_2$ denotes the vectors of variables for a system of equations. Distributional assumptions of the error terms in a system of equations are defined as the following:

$$\xi_1 | \mathbf{X} \sim N[0, 1] \tag{19}$$

$$\xi_2 | \mathbf{X} \sim N\left[0, \sigma_2^2\right] \tag{20}$$

$$Cov\left[\xi_1, \xi_2 | \mathbf{X}\right] = \sigma_{12} \tag{21}$$

where $\mathbf{X}$ is defined as a vector containing $\mathbf{X}_1$ and $\mathbf{X}_2$, $\mathbf{X} = (\mathbf{X}_1, \mathbf{X}_2)'$. Given the assumption of bivariate normal error terms where the variance of ξ_1 is normalized to 1 without loss of generality because y_1^* is a bivariate variable and given the assumption of homoscedasticity of error terms[4], the estimation can be performed by using maximum likelihood estimation. The probability that we observe y_2^* is then given by the probability that $y_1^* > 0$ multiplied by the conditional probability of y_2^* conditional on $y_1^* > 0$. Therefore the density of the known values of y_2^* is $f\left(y_2^* | y_1^* > 0\right) \Pr\left[y_1^* > 0\right]$. For non positive values of y_1^*, one do not observe any values of y_2^* and the density is the probability of y_1^* being non positive, $\Pr\left[y_1^* \leq 0\right]$. The likelihood function for the bivariate sample selection model is then defined as:

$$L = \prod_{i=1}^{n} \left\{ \Pr\left[y_1^* > 0\right] \right\}^{1-y_{1i}} \left\{ f\left(y_2^* | y_1^* > 0\right) \Pr\left[y_1^* > 0\right] \right\}^{y_{1i}} \tag{22}$$

The log-likelihood function is derived by simply taking the logarithm of the likelihood function:

[4] In other words this implies strict exogeneity of error terms.

$$\log L=\sum_{i=1}^{n}(1-y_{1i})\log\left\{\Pr\left[y_1^*>0\right]\right\}+y_{1i}\log\left\{f\left(y_2^*|y_1^*>0\right)\Pr\left[y_1^*>0\right]\right\} \quad (23)$$

As we can see from the last two equations, the log-likelihood function is having a degenerate distribution, that is a compostition of discrete distribution when $y_1^* \leq 0$ and the continuous distribution when $y_1^* > 0$. The population conditional distribution in truncated samples is considered to be normal, where mostly truncated normal of truncated Tobit regressions have been used in estimation.

Calculating the conditional mean in the sample selection model will differ from OLS conditional mean which implies the inconsistent parameter estimation of the latter method. For randomly obtained sample from the population and assuming a linearity in conditional expectation of y_i on $\mathbf{X}_i$, $\mathrm{E}[y_i|\mathbf{X}_i] = \mathbf{X}_i'\boldsymbol{\beta}$, the estimation suggests using OLS approach. However, when the selection in the sample is based on y_1 , the OLS parameter estimation might suffer from inconsistency. The conditional mean of y_2 in the sample selectivity model where one uses only a positive values of y_1, is then defined as:

$$\begin{aligned}\mathrm{E}\left[y_2|\mathbf{X},y_1^*>0\right] &= \mathrm{E}\left[\mathbf{X}_2'\boldsymbol{\beta}+\xi_2|\mathbf{X}_1'\boldsymbol{\beta}_1+\xi_1>0\right] \\ &= \mathrm{E}\left[\mathbf{X}_2'\boldsymbol{\beta}_1|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right]+\mathrm{E}\left[\xi_2|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right] \\ &= \mathbf{X}_2'\boldsymbol{\beta}_2+\mathrm{E}\left[\xi_2|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right]\end{aligned} \quad (24)$$

where $\mathbf{X}=(\mathbf{X}_1,\mathbf{X}_2)'$. Following the assumption of correlation of the error terms $\xi_1$and ξ_2, the last term on the right hand side of the conditional mean cannot be zero and therefore a sample selection needs to be taken into consideration. Given the normality assumption of error terms, Heckman proposed the correlation between the two terms in the following way:

$$\xi_2 = \sigma_{12}\xi_1 + \zeta \quad (25)$$

where ζ denotes the random variable, independent of ξ_1[5].The truncated mean of y_2 when using the previous assumption can be rewritten as:

$$\begin{aligned}\mathrm{E}\left[y_2|\mathbf{X},y_1^*>0\right] &= \mathbf{X}_2'\boldsymbol{\beta}_2+\mathrm{E}\left[\left(\sigma_{12}\xi_1+\zeta\right)|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right] \\ &= \mathbf{X}_2'\boldsymbol{\beta}_2+\sigma_{12}\mathrm{E}\left[\xi_1|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right]+\mathrm{E}\left[\zeta|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right] \\ &= \mathbf{X}_2'\boldsymbol{\beta}_2+\sigma_{12}\mathrm{E}\left[\xi_1|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right]\end{aligned} \quad (26)$$

[5] Note that the covariance between erorr terms $\xi_1$and ξ_2, σ_{12}, can be expressed as $\sigma_{12} = \rho\sigma_2$, where ρ denotes the correlation coefficient between error terms $\xi_1$and ξ_2. Following this notation one can rewritte the truncated conditional mean as:

$$\begin{aligned}\mathrm{E}\left[y_2|\mathbf{X},y_1^*>0\right] &= \mathbf{X}_2'\boldsymbol{\beta}_2+\mathrm{E}\left[\left(\rho\sigma_2\xi_1+\zeta\right)|\xi_1>-\mathbf{X}_1'\boldsymbol{\beta}_1\right] \\ &= \mathbf{X}_2'\boldsymbol{\beta}_2+\rho\sigma_2\sigma_1\mathrm{E}\left[\frac{\xi_1}{\sigma_1}|\frac{\xi_1}{\sigma_1}>\frac{-\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right]\end{aligned}$$

Using the left-truncated moments of the standard normal distribution, the expectation term of ξ_1 on the right hand side of the truncated mean of y_2 is given by:

$$\begin{aligned}
\mathrm{E}\left[\xi_1|\xi_1 > -\mathbf{X}_1'\boldsymbol{\beta}_1\right] &= \sigma_1 \mathrm{E}\left[\frac{\boldsymbol{\xi}_1}{\sigma_1}|\frac{\boldsymbol{\xi}_1}{\sigma_1} > \frac{-\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right] \qquad (27)\\
&= \sigma_1 \int\limits_{-\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1}^{\infty} z[\phi(z)/1 - \Phi(-\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1)]dz \\
&= \sigma_1 \frac{\boldsymbol{\phi}\left(-\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1\right)}{\left[1 - \Phi(-\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1)\right]} \\
&= \sigma_1 \frac{\boldsymbol{\phi}(\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1)}{\Phi(\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1)} \\
&= \sigma_1 \lambda\left(\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1\right)
\end{aligned}$$

where the third line in the expression above uses symmetry about zero of the standard normal density $\phi(\cdot)$ and $\Phi(\cdot)$ denotes the standard normal cdf[6]. The ratio of the standard normal density $\phi(\cdot)$ and the standard normal cdf $\Phi(\cdot)$, is called the inverse Mills ratio and it is denoted by $\lambda(\cdot)$. Combining the conditional expectation of error term ξ_1, with the truncated mean of y_2, the conditional expectation of positive observed variable y_2 can be rewritten as:

$$\mathrm{E}\left[y_2|\mathbf{X}, y_1^* > 0\right] = \mathbf{X}_2'\boldsymbol{\beta}_2 + \sigma_{12}\sigma_1\lambda\left(\frac{\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right) \qquad (28)$$

The conditional left-truncated expectation of y_2 implies that standard OLS estimation in the case of sample selection bias will produce inconsistent estimation of parameters of interest unless the covariance term between two errors $\xi_1$and ξ_2 is zero. The Heckman's two step approach, estimaties the omitted regressor $\lambda\left(\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1\right)$ using OLS regression estimation. As the name indicates, the Heckman's sample selection estimation can be described in two steps. First step is to use probit regression of y_1 on $\mathbf{X}_1$, where the probability that the variable y_1^* is positive is given by[7]:

$$\begin{aligned}
\Pr\left[y_1^* > 0\right] &= \Pr\left[\mathbf{X}_1'\boldsymbol{\beta}_1 + \xi_1 > 0\right] \qquad (29)\\
&= \Pr\left[\frac{\boldsymbol{\xi}_1}{\sigma_1}|\frac{\boldsymbol{\xi}_1}{\sigma_1} > \frac{-\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right] \\
&= 1 - \Phi\left(\frac{-\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right) \\
&= \Phi\left(\frac{\mathbf{X}_1'\boldsymbol{\beta}_1}{\sigma_1}\right)
\end{aligned}$$

[6] The standard normal cdf, $\Phi(\cdot)$, gives the probability of truncation when truncation is at point $\cdot$.

[7] Here I used the symmetry of the standard normal distribution about zero.

The inverse Mills ratio[8],$\lambda\left(\mathbf{X}_1'\boldsymbol{\beta}_1/\sigma_1\right)$,can then be estimated from the first step probit regression. The second step in estimation consists of the OLS estimation of y_2 on $\mathbf{X}_2$ and $\lambda\left(\mathbf{X}_1'\hat{\beta}_1/\hat{\sigma}_1\right)$ for positive values of y_2:

$$y_{2i} = \mathbf{X}_{2i}'\boldsymbol{\beta}_2 + \sigma_{12}\sigma_1\lambda\left(\frac{\mathbf{X}_1'\hat{\beta}_1}{\hat{\sigma}_1}\right) + \eta_i \tag{30}$$

where η_i is OLS error term[9]. Heckman (1979) showed that we can consistently estimate $\boldsymbol{\beta}_2$ and ρ by using the selected sample in OLS regression of y_2 on $\mathbf{X}_2$ and $\lambda\left(\mathbf{X}_1'\hat{\boldsymbol{\beta}}_1/\hat{\sigma}_1\right)$, where $\boldsymbol{\beta}_1$can be consistently estimated from the probit model[10] on the selection equation. The Heckman model can also be estimated by MLE. MLE requires that ξ_1 and ξ_2 are distributed bivariate normal with mean zero and correlation term ρ, that is $\xi_1, \xi_2 \sim N[0, 0, 1, \sigma_2^2, \rho]$. Therefore,:Therefore, the MLE estimation is not as general as the two step procedure. MLE is less robust and than the two step procedure and it is sometimes diffcult to get it converge.However, the Heckit estimator can suffer from a loss in efficiency compared to the MLE if $\xi_1$and $\xi_2$are jointly normally distributed. Nontheless, the Heckit[11] estimator is very simple to implement, it requires distributional assumptions[12] weaker than joint normality of ξ_1 and ξ_2 and these distributional assumptions can be weakened even further to permit semiparametric estimation.

3.2 The participation decision model

The participation decision is referred as a choice between working or not working. Here I illustrate the probit regression model which is the main building block for the empirical analysis. A dichotomous variable $INLF_i$ indicates whether an individual i supplies positive or zero number of working hours. In the former case $INLF_i$ equals one and zero otherwise. The analysis of labor supply in the neoclassical model assumes that the participation decision is a function of the net effective wage $(1-\tau_i)w_i$[13], a vector of household characteristics $\mathbf{Z}_i$ and other demographic variables that influence individual preferences, non-labor income of an individual's and other household income y_i and the cost

[8] The estimated inverse Mills is defined as follows: $\lambda\left(\frac{\mathbf{X}_1'\hat{\boldsymbol{\beta}}_1}{\hat{\sigma}_1}\right) = \frac{\phi(\mathbf{X}_1'\hat{\boldsymbol{\beta}}_1/\hat{\sigma}_1)}{\Phi(\mathbf{X}_1'\hat{\boldsymbol{\beta}}_1/\hat{\sigma}_1)}$.

[9] Both the OLS standard errors and heteroskedasticity robust standard errors from second step estimation equation are not correct because the truncated variance of y_2 is heteroscedastic, unless $\sigma_{12} = 0$.

[10] Probit model is simple to model and estimation is by maximum likelihood because the distribution of the data is defined by Bernoulli model. The MLE is consistent if the conditional density of dependent variable y given the regressors $\mathbf{X}$ is correctly specified. Therefore, the MLE is consistent if $p_i = \Phi(\mathbf{X}_i'\boldsymbol{\beta})$ and it is inconsistent otherwise.

[11] Maximum likelihood estimation of the parameters can be time consuming with large datasets and the Heckit estimates can provide good alternative in such cases. The estimators from a Heckit model are consistent and asymptotically normal.

[12] In the Heckit model all we need to assume is that $\xi_1$and ξ_2 are independent of independent variables with mean zero and that $\xi_2 \sim N[0, 1]$.

[13] The net effective wage is defined as the gross wage net of taxes and transfers.

of working. The labor force participation decision in its functional form can be defined as:

$$INLF_i = f((1-\tau_i)w_i, y_i, \mathbf{Z}_i) \tag{31}$$

For estimating the wage effect on the labor force participation decision, I am using the following approximation for the optimal number of hours of work h_i^{0*}, that is chosen by each individual i :

$$h_i^{0*} = \beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i \tag{32}$$

where ε_i is an error term that is assumed to be independent and normally distributed across individuals with the mean zero and variance σ_ε^2, $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$. The probability of labor force participation for an individual i is defined as:

$$\begin{aligned} \Pr(INLF_i = 1) &= \Pr(h_i^{0*} > 0) \\ &= \Pr(\beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i > 0) \end{aligned} \tag{33}$$

Assuming the particular distributional form for the error term, ε_i, we can estimate the standard probit model for the labor participation decision:

$$\begin{aligned} \Pr(INLF_i = 1|(1-\tau_i)w_i, \mathbf{Z}) &= \Phi(\beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma} + \varepsilon_i > 0) \\ &= \Phi(\varepsilon_i > -(\beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma}) \\ &= 1 - \Phi(\varepsilon_i > -(\beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma}) \\ &= \Phi(\beta \ln((1-\tau_i)w_i) + \mathbf{Z}_i'\boldsymbol{\gamma}) \end{aligned} \tag{34}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. Due to non-linearity of the functional form in the model, one needs to calculate the marginal effects at the means of regressors or at some other interesting values of the regressors in order to make valid interpretations of its partial effects. In line with the ILO definition of employment, I specified the binary labor force participation indicator to one, $INLF_i = 1$, for an individual's i who are employed or currently unemployed but actively search for employment and $INLF_i = 0$ for those who are neither unemployed nor seek employment. Focusing on the estimation of labor supply in partial equilibrium setting I have not considered the relevance of demand side of labor market. This approach opens up the field for criticism because the labor force participation decision can be influenced by the demand for work. One attempt to take into consideration the constraints on the demand side, following the approach in the literature, was to include the regional unemployment rates for each country. However, the inclusion of local unemployment rates in estimation was abandoned after finding out its very strong serial correlation with other regressors in the model.

The main interest in the model is to estimate the parameter on wage regressor, β, that represents the wage semi-elasticity of labor force participation[14]. Dividing the wage semi-elasticity by the probability of labor force participation one can obtain the wage elasticity. The estimation from the probit model follows two different treatments; first treatment is with the gross hourly wage regressor and second treatment is with the net effective wage regressor. The analysis of the incentives or disincentives of the welfare system is based on the marginal effect between the two treatments on the probability of being employed. In the following section I explain the derivation of the wage regressor. Additionally, the probit model includes other income variable, variables describing household characteristics, education and binary race variable[15]. In the literature, the marginal effects of wage and socio-demographic regressors on the probability of labor supply are differs between the two genders. Respecting these empirical findings I estimated the model separately by men and women.

3.3 Empirical wage specifications

The model outlined in the previous subsection predicts the probability for being in the workforce by using observations on actual wage or conditional wage for every individual. Typically it is not possible to observe wages for non-workers and this poses a problem for modelling behavioural responses. For those individuals who do not work I estimate the expected market wage rate that can be used in place of missing wage observations. Using the Heckman (1979) sample selection model I estimate the wage equation for a fraction of workers whose wages were observed, conditioning on the labor force participation. The two equations system is estimated as a two step Heckman selection model. The error terms from wage and selection equations are assumed to be correlated, which is also supported by the model[16]. The estimated wage equation that accounts for sample selection bias then predicts the gross hourly wage for workers and non-workers. The following estimation procedure is applied separatedly to men and women.

When estimating the labor force participation with the probit model I use two constructions, the predicted gross hourly wage and the effective net hourly wage. The effective net hourly wage is derived by subtracting taxes and transfers from the gross hourly wage. To avoid identification problems in the Heckman sample selection model, at least one regressor must be unique in both equations. Therefore the selectivity equation will contain at least one variable that is not used for the wage estimation. As the regressors on the right-hand side of the wage equation that by assumption does not have an impact on the labor force participation decision, I use age of the worker, binary indicators for education, race binary indicator and regional binary variables. For selection equation I

[14] The marginal effect of wage on the probability of supplying labor is given by β, as wage regressor is expressed in the logarithm.

[15] The detail definition of the variables is provided in the subsection A.1 in the Appendix A.

[16] See the Appendix B for a full specification of the Heckman model.

use demographic regressors like age, marital status, race, variable indicating the presence of children in particular age, regional binary variables, other income variable and binary education indicator. The exclusion restrictions have been tested with the standardized z statistic on the significance of regressors in wage and selection equation. When a particular regressor in estimation is insignificant in a preliminary regression then this variable will not be included in the estimation of the final model. I use the bootstrap method to derive the standard errors of the sampling distribution of estimated coefficients in the probit regression of the labor force participation and in computing its marginal effects. The main reason for bootstrapping comes from the fact that in the estimation I use predicted wage observations. The bootstrap method consider the sample as the population to derive properties of the sampling distribution of the estimators.

After predicting the gross hourly wage[17] I derived the second wage specification, the net effective wage. Generating the net effective wage follows this equation:

$$NEW_i = (1 - \tau_i)GRW_i \tag{35}$$

where NEW_i is the net effective wage for an individual i, GRW_i is the gross wage for an individual i and τ_i denotes the effective marginal tax rate for an individual i. Construction of the effective marginal tax rate τ_i is given by:

$$\tau_i = 1 - \frac{GRW_i - NW_i}{GRW_i} \tag{36}$$

where NW_i denotes the predicted net hourly wage, i.e. predicted gross hourly wage minus taxation. One of disadvantages of this approach is that it does not take into a consideration subtraction of possible social security transfers from the predicted gross hourly wage. Moreover, construction of τ_i does not take into account the differences between the social benefits (parental allowance, housing benefits, child benefits, maternity allowances, etc) to which an individual is entitled when employed or unemployed.

[17]The sample provides information's on total hours worked by an individual and the gross earned income from the main job and any second jobs. Both variables are measured on the weekly basis at the time of the interview. To construct total annual working hours I have multiplied weekly working hours by 52 what is the number of weeks in a year. The same approach was applied to construct the annual gross income.

4 Data

4.1 The description of the dataset

The data used in this thesis comes from the General Household Survey (GHS) conducted on an annual basis, by the Social Survey Division of the Office for National Statistics (ONS). The main aim of the survey is to collect data on a range of core topics, covering household, family and individual information on earnings as well as social and demographic characteristics[18]. This information is used by government departments and other organisations for planning, policy and monitoring purposes, and to present a picture of households, family and people in Great Britain. The GHS aims to interview all adults aged 16 or over at every household at the sampled address[19]. It uses a probability, stratified two-stage sample design. The Primary Sampling Units (PSUs) are postcode sectors, which are similar in size to wards and the secondary sampling units are addresses within those sectors[20]. Since April 1994, the GHS has been conducted on a financial year basis, with fieldwork spread evenly across the year April-March. However, in 2005 the survey period reverted to a calendar year and the whole of the annual sample was dealt with in the nine months April to December 2005[21]. Since the 2005 survey does not cover the January-March quarter, this affects annual estimates for topics which are subject to seasonal variation. To rectify this, where the questions were the same in 2005 as in 2004-05, the final quarter of the 2004-05 survey has been added (weighted in the correct proportion) to the nine months of the 2005 survey.

The dataset is representative of the population of Great Britain and contains 30,069 individual interviews in 12,802 households. The survey contains comprehensive and redundant observations about gross income, net income and wealth. Therefore the Division of ONS have already recovered gross incomes using proper tax benefit simulation for every individual which makes this dataset suitable for appropriate estimation of the labour supply. For modeling the labor supply behaviour I select a subsample of the whole population where a selected subsample do not contains individuals younger than 16 and older than 60 years old, self-employed and fully disabled people. In the labor supply models, the heterogeneity of agents behaviour becomes more difficult to estimate with the model that is previously described and that is why the sample restrictions are necessary. Individuals that are self-employed are excluded because it is difficult to explain the behaviour of self-employed individual that is not working. What is ambiguous here for the self-employment status is that we do not observe whether the individuals that are not working would have worked as a self-employed or as a dependent worker if the decision to work has been made. The rationale for other exclusion follows a disbelief that those individuals behave in the standard trade off sense between leisure and income. After filtering

[18] Office for National Statistics: November 2007
[19] Office for National Statistics: November 2007
[20] Office for National Statistics: November 2007
[21] Office for National Statistics: November 2007

out all the non-complying individuals the estimation sample consists of 9,792 individuals; 4,392 men and 5,400 women living in 6,746 households. The dataset used in estimation is summarized in the table 1.

Table 1: Summary statistics: Men and Women

	Men		Women	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Labor force participation	.9353370	.2459583	.7637037	.4248456
Age	40.13957	11.64261	40.17148	11.53118
Education	.8469945	.3600338	.8314815	.3743608
Non-white	.0810565	.2729529	.0903704	.2867382
Married	.5580601	.4966741	.5662963	.4956312
Other income	14,33169	17,32207	20,44055	29,68035
Children 0-4 Years	.1657559	.3719037	.2074074	.4054874
Children 5-15 Years	.2868852	.452359	.3461111	.4757732
Observations	4,392		5,400	

Notes: Other income represents summation of individual‘s non-labor income and income of other household members, measured after taxation in thousands of GBP.

4.2 Description of the variables

The gender specific variables are presented for males and females as the estimation is done seperately by gender. The detail definition of all the variables are described in subsection A1 of the appendix A. As we can see, male and female participation rates in the sample are 93.5 and 76.3 percent, respectively. The unemployment rates are 4.5 percent for men and 2.6 percent for women[22].This implies economical inactivity rate of 6.5 percent and 23.7 percent for men and women, respectively.

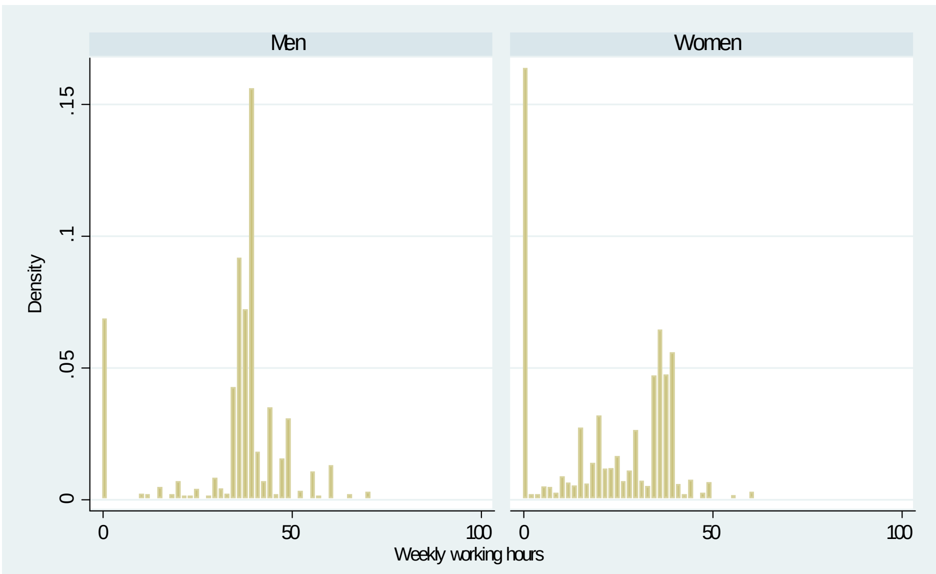
The average household member is 40 years old, with the men being about the same age as the women. About 56 percent of the individuals are married and they are living with their partners[23]. Households inhabited by males own on average 279 GBP per week while the households inhabited by females own on average 393 GBP per week. About 85 percent of men and 83 percent of women have any form of qualification while on average both genders have 11 years of education. The distribution of children aged up to 5 years and children aged from 5 up to 15 years is 16 percent and 29 percent for the households inhabitated by men.

For the households inhabitated by women the distribution of children aged up to 5 years and children aged from 5 to 15 years is 21 percent and 35 percent, respectively. The substantial difference in the labor force participation across

[22]The unemployment rate is defined as the share of the unemployed over the sum of employed and unemployed.

[23]The definition of being married presuposes that an individual is legally married and live in cohabitation with the partner.

gender is implied in total hours worked, where on average men worked more than 13 hours per week than women. The distribution of men and women weekly working hours is presented in the histogram in the the Figure 1.



Distribution of weekly working hours for men and women

As we can see a spike at zero in both distributions showing the non participation but more pronouncing spike appears for women. The distribution of working hours implies that the men tend to work mostly around the mean value of 35 hours per week (apart from non participation) whereas the women's working distribution unfold a form of part time employment. Probably there exists a degree of flexibility in employment contracts on female labor market that causes relatively non negligible distribution of working hours within the part-time region. The gross hourly wage of employed women in the sample was 10.91 GBP what is less than the gross hourly wage of employed men that amounts 15.40 GBP, on average. The distribution of the gross hourly wage of employed men shows greater inequality in comparison with women, where more than 70 percent of men are below the mean value of gross hourly wage. The skewness of gross hourly wage distribution for women is less emphasized with about 60 percent of women are below the mean value of gross hourly wage.

Non parametric density estimates are used for comparison between different gender groups. The nonparametric representation of logarithm of the gross hourly wage for men and women by histogram is less smooth than with kernel estimation. The distribution of the gross hourly wage was right-skewed and we can model logarithm of the hourly gross wage. The logarithmic wage data

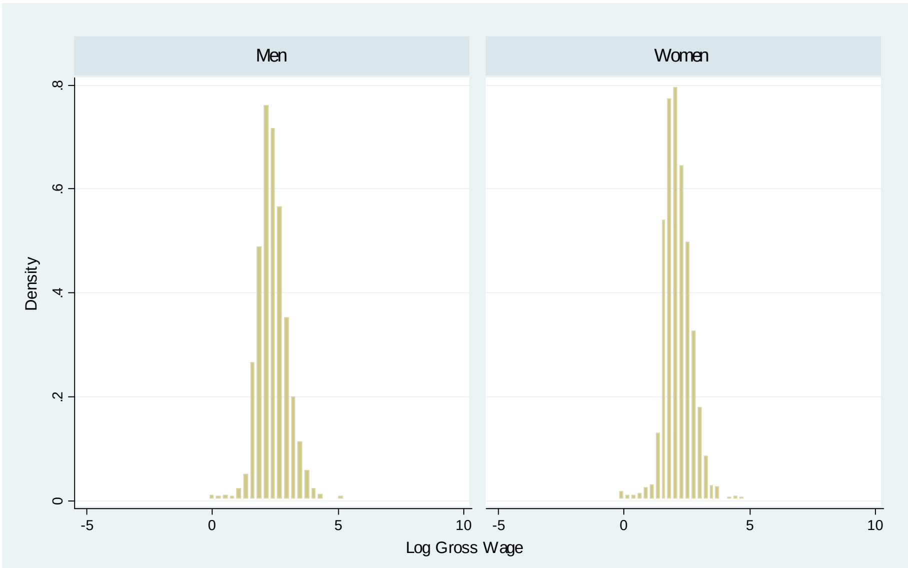


Figure 1: Histogram of the gross hourly wage for men and women

for both genders seem to be quite symmetric around the mean value. The mean of logarithmic hourly gross wage is 2.44 and 2.18 for men and women, respectively. A distribution of logarithmic gross hourly wage for men and women is represented in the Figure 2.

5 Results

This section provides the results from the Heckman model for the wage equation and the results from the participation model. I analyze the results from both models where in addition for the probit model, the marginal effects is computed and discussed.

5.1 Heckman sample selection model results

It is crucial to check whether the selection in Heckit model is based on unobservable characteristics. If the error terms, $\xi_1$and ξ_2, are correlated in the Heckit model after conditioning on other right hand side variables, then the selection two step approach is justified. The participation and wage equation implies that unobserved factors that make someone to work more may also make them to work longer that it would be predicted. The presence of unobservable characteristics has been tested in the model and the results confirmed presence of sample selection bias.

Table 8 and table 9 presents the estimated parameters in log-linear model for the gross wage, that take into account for potential sample selection bias[24]. Using the Heckit model I focus on modeling logarithmic wage for those in employment. The inverse Mills ratio term is statistically significant for men, $z = -3.10$ and for women, $z = -2.61$ which implies the presence of sample selection bias. Moreover, the magnitude of the inverse Mills ratio term is almost one for men, $\hat{\rho} = -0.985$ and it is lower for women, $\hat{\rho} = -0.232$. The t-statistics on regional indicators in the selection equation are mostly insignificant either for men or women, which implies that regions does not affect the participation in labor force. However, the regional binary variables are highly significant in wage equation for both genders. All demographic variables except the educational binary variable for women and other income variable are statistically significant and therefore have their impact on the wage offered. The presence of children in the household does not seem to have an effect for male participation[25]in the market. In contrast with men, the presence of children has a negative and significant effect for women. Regarding marital status, there is no effect on participation for either men or women.

After predicting the logarithmic wages for men and women by the Heckit model, one can make the comparison of predicted wages and actual wages for those that participate in the labor market. The results for working men in the table 10 imply that the average predictions of the logarithmic wages from the Heckit model are exactly the same in mean as the actual wages. The last line

[24] The OLS standard errors and heteroscedasticity robust standard errors in the Heckit model are not correct because the error term, η_i, suffers from heteroscedasticity since the truncated variance of the dependent variable is heteroscedastic. Although, Heckman (1979) provided the expressions for the correct standard error they are not used in estimation. Rather, I used the empirical bootstrap method with 500 replications to correct for the heteroscedasticity of errors.

[25] The presence of children until 4 years old has a statistically significant effect at 10 percent for men participation in the market.

in table 10 shows that without taking the sample selection bias into account, on average logarithmic wages for working men are over predicted. The same predictions have been made for woman and the results are summarized in table 11. Again, the average predictions of the logarithmic wages for women from the Heckit model are perfectly matching with the mean of observed wages. Comparing the mean linear predictions of the logarithmic wage for women with the actual logarithmic wage reveals that the former wages are over predicted on average. When comparing the mean of linear over prediction from the mean of actual wages by gender, for women this accounts 0.45 GBP while for men accounts 1.72 GBP.

The Heckit conditional wage predictions are made for all individuals in the sample but they can be compared only with observed wages for those in employment. However, we can be interested in comparing the mean of wages for all men and women whether they participate in paid work or not. The mean of the Heckit conditional predictions of wages and the mean of observed wages for all men in the sample are presented in table 12[26]. One can note that the predictions from the Heckit model for the gross hourly wages are similar to the mean of observed gross hourly wages. The mean of the Heckit predicted gross hourly wage for those men in paid work are larger for about 2.53 GBP than the same prediction for all men in the sample. This result is nevertheless expected because when predicting the gross hourly wage for all men by the Heckit method, the cumulative distribution function that measures the probability of being in the labor force is smaller than one.

Comparing the mean gross hourly wages predicted by the Heckit and actual gross hourly wage shows that these two are very similar for women. On average the Heckit predicted gross hourly wage for employed women are larger then the Heckit prediction by about 2.63 GBP. These results are presented in the table 13.

5.2 The participation decision model results

The wage equation from the Heckit model predicted the wages for non-workers whose wages were not observed. The actual and predicted gross hourly wages were used to derive the effective net hourly wages[27] that will be used as the main regressor in estimating the labor force participation rates. The probability of working is estimated with the probit model and the results are presented in the table 14 and table 15 for the gross wage specification and in the table 16 and table 17 for the net effective wage specification.

There are two specifications of the probit model, one with the logarithmic gross hourly wage and the other with the logarithmic effective net hourly wage. Comparing the goodness of fit with χ^2 statistics (of the Wald test whether all coefficients except the constant) across two specifications of a model, the

[26] One should note that these predictions are in wage levels not in the logarithm. For comparison, observed wage for those who are determined by participation equation as non-participants, are set to zero.

[27] As it was explained in part 3.3.

specification with the effective net wage performs approximately the same as the specification with the gross wage and that is for both gender. The comparison of fit based on the pseudo-R^2 shows equivalence for both specifications within the gender but marginally better performance for women when comparing between gender. The positive sign on wage coefficients for men and negative coefficients for women indicate that the probability of supplying labor will increase for men and decrease for women if there is a change in the wage. One reason for that might be that men will substitute away leisure for work due to greater substitution than income effect, and women will do the opposite by substituting work for leisure due to greater income effect. The positive sign on age coefficient implies that labor supply is increasing with age but there is a point above which the age has negative effect on the probability of working (marginal decreasing returns on age are present). The effect of education on probability of working is significant only for women and positive impliying that educated women are more likely to work in contrast with women without education. The presence of children reduces men's and women's probability of employment and the effect decreases with the children's age. However, the presence of children older than four years has no effect on men's decision to work. As probably expected, non-labor income has negative effect on the probability of employment, although the effect is insignificant for women and marginally significant for men. Positive coefficient on marital status indicates higher probability of working for married people than non-married, however there is no effect for women. The probability of working increases for white men and women in contrast with non-whites'[28].

5.3 Elasticity results

While one can draw inferences about the sign and significance of the regressors from the probit model by looking at the coefficients, the magnitude of these effects cannot be read directly. Therefore, the marginal effects need to be calculated at either at the mean or other interesting value of variables. The marginal probit effects are not constant like in the usual OLS regression model but they differ in size due to the non-linearity of the probit model. After estimating the probit model for labor force participation, the marginal effects are calculated and presented in the table 2 and table 3 for men and women, respectively.

These effects were calculated at the means of the variables[29]. However, the means of the marginal effects computed for each individual is presented in addition. The first row of the table 2 and table 3 shows the wage semi-elasticity

[28] The effects on country binary variables are not significant for women. The joint and individual significance of the binary variables, Wales and Scotland were checked by likelihood ratio test and z-statistics. The former test showed no significant joint effect at 10 percent significance level for women's sample.

[29] Marginal effects of continuous regressors are computed by using the probability density function at the mean values of regressors. Marginal effects of discrete regressors are computed as a change in the normal cumulative density functions evaluated at the zero and one for the particular discrete variable for which the change is made.

of labor supply[30]. When comparing either the gross wage semi-elasticity or the net effective wage semi-elasticity across gender, they are both larger for men than for women. The gross wage has significant effect on male labor force participation decision implying that a one percent increase in gross hourly wage increases the probability of supplying labor by 0.0951 percentage point for men with the average characteristics in the sample.

In contrast with men, increasing the gross wage will reduce the probability of supplying labor for women by 0.0285 percentage point, however the effect is not significant. Calculating the mean marginal effects[31], by dividing the wage semi-elasticities with the predicted probability of labor force participation at means of variables, the gross wage elasticities are 0.1046 and -0.0373 for men and women, respectively[32].

Evaluating the marginal effect of additional age at the average value of variables in the sample[33] increases the probability of supplying labor for 0.02 and 0.06 percentage point for men and women, respectively. The marginal diminishing effect of age is significant and it present for men and women. While education does not have significant effect on male labor supply, its effect is significant and pronounced for women implying that the probability of being employed for women with at least high school educational attainment[34] is by 0.12 higher than for women without high school. The negative marginal effect on race binary indicator implies that the probability of labor supply is higher by 0.09 and 0.20 for white men and women, conditional on the averages of other characteristics. The effect of non-labor income, although not significant for both genders, has the expected sign. The probability of supplying labor

[30] Wage semi-elasticity of labor supply, ω, is defined as the following expression:

$$\omega = \frac{\partial \Pr(INLF = 1)}{\partial \log wage} = \frac{\partial \Pr(INLF = 1)}{\partial wage} \times wage$$

that can be interpreted as the wage marginal effect on the probability of supplying labor,

$$mfx = \frac{\partial \Pr(INLF = 1)}{\partial \log wage} = \phi\left(\gamma \ln(wage) + \mathbf{X}\boldsymbol{\beta}\right) \times \gamma$$

where $\phi(\cdot)$ denotes the standard normal density function. We can interpret these effects as: a one percent increase in wage, increases the probability of supplying labor by $(1/100) \times mfx$.

[31] Mean wage marginal effect or wage elasticity can be expressed as:

$$\begin{aligned} \mu &= \frac{\partial \Pr(INLF = 1)}{\partial wage} \times \frac{wage}{\Pr(INLF = 1)} \\ &= \frac{\omega}{\Pr(INLF = 1)} \end{aligned}$$

The wage elasticity is calculated by using ω and the predicted probability of labor force participation, $\Pr(INLF = 1)$.

[32] The wage elasticity for men is close to wage semi-elasticity because the predicted labor force participation is 0.9088 or 90.88 percent. While for women, the wage semi-elasticity is larger then the wage elasticity due to the predicted labor force participation of 0.7643 or 76.43 percent.

[33] The average age for men and women in the sample is approximately the same, that is 40 years old.

[34] Again the effect is measured at the average values of variables in the sample.

Table 2: Marginal Effects-Men

	Gross Wage		Net Effective Wage	
Variable	Mfx	Std error	Mfx	Std error
Log Wage	0.0951	0.0516	0.1043	0.0525
Age	0.0236	0.0037	0.0232	0.0041
Age^2	-0.0003	0.0000	-0.0003	0.0000
Education^a	0.0102	0.0175	0.0090	0.0172
Non-white^a	-0.0944	0.0225	-0.0973	0.0220
Other income	-0.0006	0.0002	-0.0006	0.0002
Children 0-4 Years^a	-0.0272	0.0154	-0.0271	0.0152
Children 5-15 Years^a	-0.0138	0.0111	-0.0138	0.0117
Married^a	0.0760	0.0114	0.0761	0.0114
N		4,392		4,392
Log-likelihood		-1383.6852		-1383.6771
$\chi^2_{(9)}$		275.92		275.93

Notes: Marginal effects computed at the means of regressors. Discrete change denoted by a. Statistical significance is calculated using bootstrap standard errors, 500 replications.

Table 3: Marginal Effects-Women

	Gross Wage		Net Effective Wage	
Variable	Mfx	Std error	Mfx	Std error
Log Wage	-0.0285	0.0617	-0.0152	0.0730
Age	0.0611	0.0054	0.0603	0.0054
Age^2	-0.0008	0.0001	-0.0008	0.0001
Education^a	0.1205	0.0299	0.1146	0.0285
Non-white^a	-0.1988	0.0250	-0.2006	0.0238
Other income	-0.0003	0.0002	-0.0003	0.0003
Children 0-4 Years^a	-0.3318	0.0187	-0.3319	0.0184
Children 5-15 Years^a	-0.1900	0.0154	-0.1898	0.0154
Married^a	0.0034	0.0132	0.0035	0.0130
N		5,400		5,400
Log-likelihood		-2707.2384		-2707.3228
$\chi^2_{(9)}$		805.70		805.53

Notes: Marginal effects computed at the means of regressors. Discrete change denoted by a. Statistical significance is calculated using bootstrap standard errors, 500 replications.

decreases for men and women that have children while the effect is far more intense for women than the men. Probability that a female with the average characteristics in the sample supply labor is lower by 0.33 if the children below for years old is present in the household. While marital status has no significant effect for women‘s labor supply, married men‘s have higher probability of being participating in the labor force than unmarried.

The following results are based on the second specification using net effective wage rate and evaluating marginal effects at the average of regressors. The semi-elasticities of labor force participation with respect to net effective wage are larger than the semi-elasticities with respect to gross wage, for men and women. The effect is significant for men and implies that a one percent increase in net effective wage increases the probability of supplying labor by 0.1043 percentage point. For women the semi-elasticity is negative, implying that one percent rise in net effective wage decreases the probability of labor supply by 0.0152 percentage point. However, the effect for women is insignificant at even 10 percent significance level. The net effective wage elasticities calculated as mean marginal effects are 0.1148 and -0.0199 for men and women, respectively. Again, the wage elasticity is closer to wage semi-elasticity for men than for women because the predicted probability of labor force participation is larger for men than for women. The marginal effects of socio-demographic characteristics on labor force participation are the same magnitude and sign in net effective wage specification as for the gross wage specification. The marginal effect of education in net effective wage specification is marginally lower than with gross wage specification, for both gender. The probability of supplying labor for men and women with white ethnic background is marginally larger in net wage specification than with gross wage specification in comparison with non-whites.

Analyzing the wage elasticities for different wage specification, the net effective wage elasticities are larger than the gross wage elasticities for both gender, although wage elasticities show no significant effect on labor supply for women. One reason for greater net effective wage elasticities can be determined by greater equality of net effective wage distribution among the individuals. This effect can be achieved by marginal effective tax rate created by a state or local authorities when seeking for a greater contributions in social transfers and progressive taxation of personal income.

Hypothetically assuming that all individuals in male sample and female sample are married, the following results are obtained by computing the wage semi-elasticity of labor supply. That is to say, these marginal effects are measuring the labor supply response to both wage specifications when there is no unmarried male or female in the sample. Comparison of the predicted probabilities of labor supply for married individuals are than compared to the predicted probabilities of labor supply that are measured on the averages of the variables. The difference between the marginal response of two wage specifications in hypothetical example stays with the same sign and magnitude[35] as in the difference

[35] However, the difference between the gross and the net effective marginal effects becomes

Table 4: Marginal Effects for Married-Men

Variable	Gross Wage Mfx	Gross Wage Std error	Net Effective Wage Mfx	Net Effective Wage Std error
Log Wage	0.0718	0.0361	0.0787	0.0394
Age	0.0178	0.0033	0.0175	0.0033
Age^2	-0.0003	0.0000	-0.0002	0.0000
Education^a	0.0078	0.0138	0.0068	0.0140
Non-white^a	-0.0743	0.0195	-0.0766	0.0187
Other income	-0.0004	0.0002	-0.0004	0.0002
Children 0-4 Years^a	-0.0207	0.0111	-0.0207	0.0117
Children 5-15 Years^a	-0.0104	0.0081	-0.0105	0.0083
N		4,392		4,392
Log-likelihood		-1383.6852		-1383.6771
$\chi^2_{(9)}$		275.92		275.93

Notes: Marginal effects computed at the means of regressors. Discrete change denoted by a. Statistical significance is calculated using bootstrap standard errors, 500 replications.

Table 5: Marginal Effects for Married-Women

Variable	Gross Wage Mfx	Gross Wage Std error	Net Effective Wage Mfx	Net Effective Wage Std error
Log Wage	-0.0284	0.0617	-0.0152	0.0736
Age	0.0608	0.0054	0.0601	0.0055
Age^2	-0.0008	0.0001	-0.0008	0.0001
Education^a	0.1202	0.0305	0.1142	0.0324
Non-white^a	-0.1984	0.0250	-0.2001	0.0250
Other income	-0.0003	0.0002	-0.0003	0.0002
Children 0-4 Years^a	-0.3311	0.0177	-0.3312	0.0186
Children 5-15 Years^a	-0.1892	0.0150	-0.1893	0.0150
N		5,400		5,400
Log-likelihood		-2707.2384		-2707.3228
$\chi^2_{(9)}$		805.70		805.53

Notes: Marginal effects computed at the means of regressors. Discrete change denoted by a. Statistical significance is calculated using bootstrap standard errors, 500 replications.

in the marginal responses measured at the average of variables. However, the magnitude of marginal effects for both wage specifications are smaller when assuming only married men relatively in comparison with the average value for marital status variable in the sample. The results are presented in table 4 and table 5.

A one percentage point rise in gross wage increases the probability of supplying labor by 0.0718 percentage point for men in the hypothetical example, while the same effect was 0.0951 when measuring the effect on the average of marital status variable. The disincentive effect by comparing these two scenarios is 25 percent. For net effective wage specification, a one percent increase in wage for men, raises the probability of labor supply by 0.0787 in hypothetical case, while on the average of marital status variable the same effect was 0.1043. The disincentive effect of these two scenarios is 25 percent. The marginal wage effects on the predicted probability of labor supply in the hypothetical scenario for women stay the same as the marginal wage effects on the predicted probability of labor supply when the effects are calculated at the means of variables. The estimated effects of other socio-demographic characteristics of labor force participation for both wage specifications and across genders, are the same sign and approximately the same size in two scenarios that were recently presented.

Illustration of marginal effects of marital status on labor supply over the whole sample distribution is presented by computing the predicted probabilities of labor force participation. Cumulative distribution function is evaluated at the sample means of regressors and with the two values for variable representing marital status, where estimated coefficients of variables follow the coefficients estimated from the probit model. Figures 3 and 4 presents the predicted probabilities as a function of wage for both wage specifications and across both genders. The marginal effect of variable indicating the marital status is given by difference between the two functions.The probability that the labor force participation will increase for men after marriage is substantially greater for men with low level of wages than those with high level of wages. However, over the whole wage distribution, the probability of supplying labor will be greater for married than for unmarried men. At around of net effective wage level that equals 4 GBP (per hour), the estimated probability of supplying labor will be 72 percent for unmarried men and 85 percent for married men. At the wage level of around 15 GBP, the estimated probability of labor supply is 91 and 96 percent for unmarried and married men, respectively. The marginal change in the estimated probability of being employed does not differ for female marital status over the wage distribution. For every wage level the probability of being employed is higher for married than the unmarried women. At the net effective wage level of 4 GBP the predicted probability of working is around 77 percent and it is marginally different between married and unmarried women. Interestingly, at the higher wage level of around 9 GBP, the predicted probability of working falls by approximately 1.5 percentage points for unmarried women and by 1.2 percentage points for married women.

marginally smaller when assuming all married men in the sample.

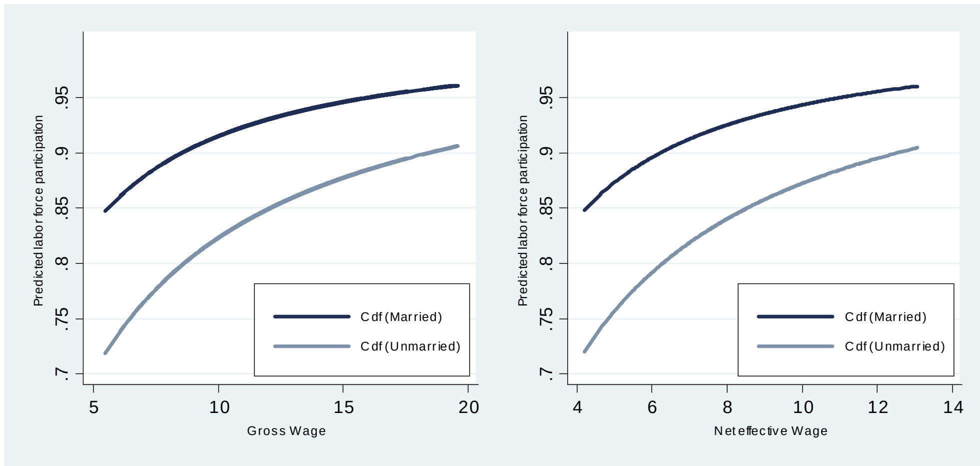


Figure 2: Predicted labor force participation rates for married and unmarried men

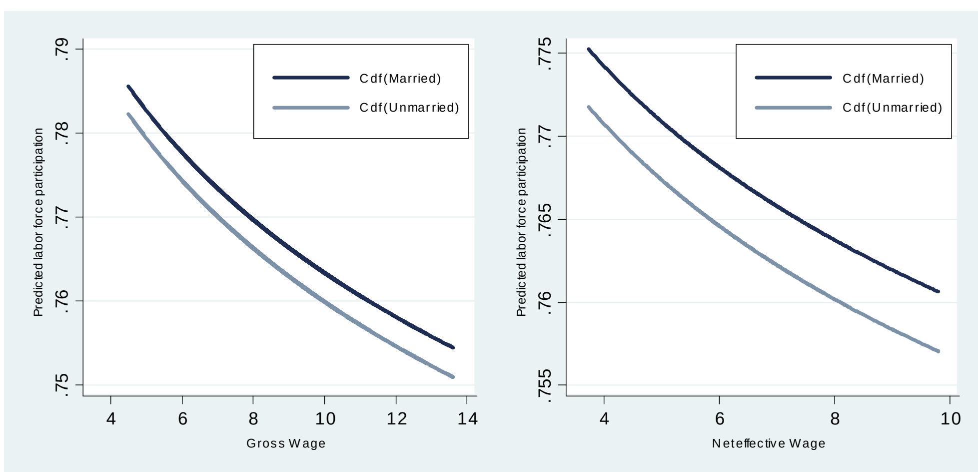


Figure 3: Predicted labor force participation for married and unmarred women

Table 6: Marginal Effects by Gross Wage and Gender

Wage Quartile	Men Wage (GBP)	Mfx	Women Wage (GBP)	Mfx
Q1	Below 8.2293	0.7255	Below 6.2644	0.0660
Q2	Below 9.4743	0.8526	Below 7.1832	-0.4504
Q3	Below 10.3399	0.5585	Below 7.7168	-0.3444
Q4	Above 10.3399	0.0904	Above 7.7168	0.0283
All		0.1047		-0.0373

Notes: Averages of marginal effects in each quintile. Statistical significance is calculated using bootstrap standard errors, 10 replications.

The marginal effects presented so far are evaluated at the means of the variables to illustrate the partial effects of an individual with the average characteristics on the probability of labor supply. Table 6 and table 7 represents the estimated wage semi-elasticities for given quartiles of hourly wage.

The semi-elasticities in these two tables are computed within quartiles on averages of regressors and at the end total averages of the marginal effects are evaluated for each individual. When comparing the total marginal effects presented in the last row of these two tables with the marginal effects in the table 2 and table 3, we can notice that the difference in computing marginal effects at means or means of marginal effects is negligible. Computing the marginal effects at means is preferable for having the correct standard errors that were obtained through the bootstrap method. The wage semi-elasticity decreases with the wage levels for both specifications and both genders when comparing the first and the fourth quartile but the results for the second and third quartile are more ambiguous. For both specifications and both genders, the wage elasticities in the second and third quartiles are more pronounced than the other quartiles. The cross-quartile differences are more pronounced in absolute values for men than for women for gross wage specification but the opposite is true for the net effective wage specification. The semi-elasticity of labor force of men with respect to the effective net wage in the first quartile is, in absolute terms more than twice the wage semi-elasticity in forth quartile, while for gross wage specification the marginal effect in first quartile is eight times the response in fourth quartile. A one percent increase in the gross wage raises the labor force participation of men in the first quartile by 72.55 percentage points, which is almost seven times the overall average marginal response. In the net effective wage specification, a one percent increase in the wage, increases the labor force participation of men in the first quartile by 9.89 percentage points, which is below the overall average marginal response.

The semi-elasticity of labor force of women with respect to the effective net wage in the first quartile is about four times greater than the wage semi-elasticity

Table 7: Marginal Effects by Net Effective Wage and Gender

Wage	Men		Women	
Quartile	Wage (GBP)	Mfx	Wage (GBP)	Mfx
Q1	Below 8.2293	0.0989	Below 6.2644	0.3204
Q2	Below 9.4743	0.4116	Below 7.1832	-0.1003
Q3	Below 10.3399	0.4593	Below 7.7168	-0.5305
Q4	Above 10.3399	-0.0402	Above 7.7168	0.0882
All		0.1148		-0.0199

Notes: Averages of marginal effects in each quintile. Statistical significance calculated using bootstrap standard errors, 500 replications

in fourth quartile, while for gross wage specification the marginal response in the first quartile is three times greater that the response in fourth quartile. A one percent increase in the gross wage raises the labor force participation of men in the first quartile by 6.60 percentage point, which is twice in absolute terms than the overall average marginal effect. Considering the net effective wage specification, a one percent increase in the wage increases the labor force participation of women in the first quartile by 32.04 percentage point, which is, in absolute terms is about sixteen times the overall average marginal effect.The wage -elasticity of women is distributed more equally within quartiles with the gross wage semi-elasticity ranges in the absolute terms from 0.0660 in the first quartile to 0.0283 in the forth quartile, the net effective semi-wage elasticity range is from 0.3204 to 0.0882 in absolute terms. The difference between the gross and net effective wage elasticities measured with the overall average marginal effect is an evidence for the Britain‘s improving welfare system. The system of taxes, social security contributions and social benefits encourages the labour force participation more than in the case when this incentives will not be present. Computing the difference between the marginal effects for the gross and net effective wage specifications, the tax-benefit system encouragements are larger for women[36] than for men. The marginal effect of the effective net wage on labor force participation is larger than the effect of the gross wage by 47 percent for women while both elasticities are negative. This means that the welfare system disincentives are lower than if we consider no existence of such a system. For men, the marginal effect of net effective wage is larger than the effect of the gross wage by 10 percent. In contrast with women, this net marginal effect is positive for males, implying the existence of welfare incentives. The interpretation of the differences between the two wage specifications across the wage quartiles is more ambiguous because for men all four wage quartiles show the disincentive effect of welfare system while the overall effect shows the opposite. However, the comparison of the results from overall marginal effect differences

[36] However, this is only true when measuring the difference in a way of reducing the disincentives on wage marginal effects for women. Nevertheless, the net effective wage marginal effect for women is larger than the gross wage marginal effect but its sign is negative.

among the gross and net effective wage, the Britain's welfare system reduces the disincentives for women and increases incentives for male labor supply. As previously stated, the estimated effects of other social and demographic determinants of labor force participation shows similar effects to those reported in the literature. Alternative determinant of income that is earned by the workers are introduced with the other income covariate. Therefore, the coefficients on the other income variable captures the income effect that appears as negative for both gender, although very small in magnitude and insignificant for women. The effect of education is positive on labor force participation for women, while the effect of children is more negatively pronounced for women than for men. The sign and significance of the marginal effects are very similar for two specifications within the gender. The estimated wage elasticities are negative and small for women and larger for men, are contrasting recent findings that the overall wage sensitivity for women is greater than for men.

6 Conclusion

In this thesis I have analyzed the performance of the participation decision model by examining the importance of the extensive margin of labor supply for men and women using the General Household Survey that collects data about private households in Great Britain. While wages for those who do not work are not observed, I follow Heckman (1979) and estimate a wage equation controlling for the selection into employment. I estimate wage semi-elasticity and wage elasticity of labor force participation using the predicted gross hourly wages for everybody in the sample. In the second specification, I estimate wage semi-elasticity and wage elasticity with respect to the net effective wage, which is generated from the gross wage but taking into account the taxes and benefits for each individual in the sample. I find that a one percent increase in the effective net wage increases the male labor force participation rate by a 0.1043 percentage point and decreases the female labor force participation rate by 0.0152 percentage point. When I use the gross wage specification, the wage semi-elasticities are 0.0951 for men and -0.0285 for women. However, both the gross and the net effective wage semi-elasticities are not significant even at 10 percent significance level.

Calculating the mean marginal effects (wage elasticity), by dividing the wage semi-elasticity with the predicted probability of labor force participation at means of regressors , the gross wage (the net effective) elasticities are 0.1046 (0.1148) and -0.0373 (-0.0199) for men and women, respectively. Wage elasticities are closer to wage semi-elasticities for men than for women because the predicted labor force participation rate is closer to one for men then for women. The following results imply that for men the marginal effect of the net effective wage on labor force participation is higher than the effect of gross wage by 10 percent, which I interpret as existence of welfare system incentives. For women, the marginal effect of the net effective wage on labor force participation is higher than the effect of gross wage by 47 percent, although both effects were negative. This implies that the welfare system disincentives for women are lower compared to the case of no welfare system. The results are more ambiguous to interpret when the wage semi-elasticities are computed for a particular wage quartile. The wage semi-elasticity decreases with the wage levels for both wage specifications and for both genders when comparing the first and the fourth quartile but the results for the second and third quartile are more ambiguous. For both wage specifications and for both genders, the wage elasticities in the second and third quartiles are more pronounced than the other quartiles.

Assuming that all individuals in the sample are married, I computed the wage semi-elasticity of labor supply for this hypothetical example. The difference between the marginal response of two wage specifications in hypothetical example stays with the same size and sing as in the difference in the marginal responses measured at the average of variables. The estimated effects of social and demographic variables on labor force participation show similar effects that can be find in the literature. The effect of education has positive effect on labor force participation for women. The income effect has negative effect on the probability of supplying labor, although the effect is relatively small in magnitude and significant only for men. The effect of children is negative across both genders and more negatively pronounced for women, while the effect deteroiorates with the children's ages. The probability that the labor force participation will increase after marriage is greater for men with low level of wages than those with high level of wages. Over the whole wage distribution, the probability of supplying labor will be greater for married than for unmarried men. The marginal change in the estimated probability of being employed does not change for women's marital status over the whole wage distribution but again for every wage level, the probability of being employed is higher for married than for unmarried women.

References

Amemiya, T. (1994), *Introduction to Statistics and Econometrics,* Harvard University Press.

Arrufat, J. L. & Zabalza, A. (1986), 'Female Labor Supply with Taxation, Random Preferences and Optimization Errors', *Econometrica* 54(1), 47-64.

Ashenfelter, O. & Heckman, J. (1973), 'Estimating labor supply functions', *in* G. G. Cain &H. W. Watts, egs, 'Income Maintenance and Labor Supply', Chicago, Markham, pp. 265-278.

Bičakova, A., Slacalek, J. & Slavik, M (2008), 'Labor Supply after Transition: Evidence from the Czech Republic', *Czech Journal of Economics and Finance* 61(4), 327-347.

Blomquist, N. (1983), 'The Effect of Income Taxation on the Labour Supply of Married Men in Sweden', *Journal of Public Economics* 22, 169-197.

Blundell, R., Bozio, A. & Laroque, G. (2011), 'Labour Supply and the Extensive Margin', *American Economic Review* 101(3), 482-486.

Blundell, R., Ham, J. & Meghir, C. (1987), 'Unemployment and Female Labor Supply', *Economic Journal* 97(388a), 44-64.

Blundell, R., Duncan, A. & Meghir, C. (1992), 'Taxation in Empirical Labor Supply Models: Lone Mothers in the UK', *Economic Journal* 102(411), 265-278.

Blundell, R., Duncan, A. & Meghir, C. (1998), 'Estimating Labor Supply Responses Using Tax Reforms', *Econometrica* 66(4), 827-861.

Blundell, R. & Macurdy, T. (1999), Labor Supply : A Review of Alternative Approaches, *in* O. Ashenfelter & D. Card, eds, 'Handbook of Labor Economics', Vol. 3, North Holland, pp. 1559-1695.

Blundell, R., Duncan, A., McCrae, J. & Meghir, C. (1999), 'Evaluating in-work Benefit Reform: The Working Families' Tax Credit in the UK', *Discussion paper*, paper presented to the Institute for Poverty Research Conference, North Western University.

Blundell, R., MaCurdy, T. & Meghir, C. (2007), Labor Supply Models : Unobserved Heterogeneity, Nonparticipation and Dynamics, *in* J. Heckman & E. Leamer, eds, 'Handbook of Econometrics', Vol. 6A, North Holland, pp. 4667-4775.

Blau, F. & Kahn, L. (2007), 'Changes in the Labor Supply Behavior of Married Women: 1980-2000', *Journal of Labor Economics* 25(3), 393-438.

Brown, C. V., Levin, E. & Ulph, D. T. (1976), 'Estimates of Labour Hours Supplied by Married Male Workers in Great Britain', *Scottish Journal of Political Economy*, 23(3), 261-277.

Burtless, G. & Hausman, J. A. (1978), 'The effect of Taxation on Labor Supply: Evaluating the Gary Negative Income Tax Experiment', *The Journal of Political Economy* 86(6), 1103-1130.

Cameron, A. C. & Trivedi, P. K. (2005), *Microeconometrics*, Cambridge University Press.

Cameron, A. C. & Trivedi, P. K. (2009), *Microeconometrics Using Stata*, Stata Press.

Callan, T., Van Soest, A. & Walsh, J. R. (2007), 'Tax Structure and Female Labor Force Participation: Evidence from Ireland', *Working Paper 208, Economic and Social Research Institute (ESRI).*

Cogan, J. (1981), 'Fixed Costs and Labor Supply', *Econometrica* 49(4), 945-964.

Creedy, J. & Duncan, A. S. (2002), 'Behavioural microsimulation with labour supply responses', *Journal of Economic Surveys* 16(1),1–39.

Creedy, J. & Kalb, G. (2005), 'Discrete Hours Labour Supply Modelling: Specification, Estimation and Simulation', *Journal of Economic Surveys* 19(5), 697-734.

Dilnot, A. & Duncan, A. (1992), 'Lone Mothers, Family Credit and Paid Work', *Fiscal Studies* 13, 1-21.

Dooley, M. D. (1982), 'Labor Supply and Fertility of Married Women: An Analysis with Grouped and Individual Data from the 1970 U.S. Census', *Journal of Human Resources 17*, 499-532.

Eissa, N. & Liebman, J. (1996). 'Labor Supply Response to the Earned Income Tax Credit', *Quarterly Journal of Economics* 61(2), 605-37.

Eissa, N, Kleven, H. & Kreiner, C. T. (2004), 'Evaluation of Four Tax Reforms in The United States: Labor Supply and Welfare Effects for Single Mothers', *NBER Working Paper* 10935.

Flood, L., Hansen, J. & Wahlberg, R. (2004). 'Household Labor Supply and Welfare Participation in Sweden'. *Journal of Human Resources*, 39(4), 1008 -1032.

Gronau, R. (1974), 'Wage Comparisons - A Selectivity Bias, *Journal of Political Economy* 82(4), 1119-1143.

Hall, R. E. (1973), 'Wages, Incomes and Hours of Work in the U.S. Labor Force', *in* G. G. Cain & H. W. Watts, eds, 'Income Maintenance and Labor Supply', Chicago, Markham, pp.102-162.

Hausman, J. (1981), 'Labor Supply', *in* H. Aaron and J. Pechman, eds, 'How Taxes Affect Economic Behavior'. Washington, D.C.: The Brookings Institution, pp. 27-72.

Heckman, J. (1974), 'Shadow Prices, Market Wages, and Labor Supply', *Econometrica* 42(4), 679-694.

Heckman, J. (1979), 'Sample Selection Bias as a Specification Error', *Econometrica* 47(1), 153-161.

Heckman, J. (1980), Sample Selection Bias as a Specification Error', *in*: J. Smith, eds, 'Female labor supply', Princeton, N.J., Princeton University Press, pp.206-248.

Heckman, J. (1993), 'What Has Been Learned About Labor Supply in the Past Twenty Years?', *American Economic Review* 83(2), 116-121.

Keane, M. & Moffitt, R. (1998), 'A Structural Model of Multiple Welfare Program Participation and Labor Supply', I*nternational Economic Review* 39(3), 553-589.

Keane, M. (2009), 'Simulated Maximum Likelihood Estimation Based on First Order Conditions', *International Economic Review* 50(2), 627-675.

Keane, M. (2011), 'Labor Supply and Taxes: A Survey', *Journal of Economic Literature*, 49(4), 961-1075.

Killingsworth, M. & Heckman, J. (1986), 'Female Labor Supply: A Survey', *in* O. Ashenfelter & R. Layard, eds, 'Handbook of Labor Economics', Vol. 1, North-Holland, pp. 103-204.

Kosters, M. (1969), 'Effects of an Income Tax on Labor Supply', *in* A. Harberger & M. Baily, eds, 'The Taxation of Income from Capital', The Brookings Institution.

Layard, R. (1978), 'Hours Supplied by British Married Men with Endogenous Overtime', *Discussion Paper* 30*, Centre for Labour Economics, London School of Economics.*

MaCurdy, T., Green, D. & Paarsch, H. (1990), 'Assessing Empirical Approaches for Analyzing Taxes and Labor Supply', *Journal of Human Resources* 25(3), 415-490.

Masters, S. & Garfinkel, I. (1977), 'Estimating the Labor Supply Effects of Income-maintenance Alternatives', I*nstitute for Research on Poverty Monograph Series New York, Academic Press.*

Mroz, T. A. (1987), 'The Sensitivity of an Empirical Model of Married Women's Hours of Work to Economic and Statistical Assumptions', *Econometrica* 55(4), 765-799.

Pencavel, John (1986), 'Labor Supply of Men: A Survey', *in* O. Ashenfelter and R. Layard, eds, 'Handbook of Labor Economics', Vol. 1, North-Holland, pp. 3-102.

Moffitt, R. (1992), 'Incentive Effects of the U.S. Welfare System: A Review', J*ournal of Economic Literature*, 30(1), 1-61.

Nakamura, A. & Nakamura, M. (1981), 'A Comparison of the Labor Force Behavior of Married Women in the United States and Canada, with Special Attention to the Impact of Income Taxes', *Econometrica* 49(2), 451-490.

Office for National Statistics. Social and Vital Statistics Division, *General Household Survey, 2005* [computer file]. *2nd edition*. Colchester, Essex: UK Data Archive [distributor], November 2007. SN:5640, http://dx.doi.org/10.5072/UKDA-SN-5640-1.

Saez, E. (2002), 'Optimal Income Transfer Programs : Intensive Versus Extensive Labor Supply Responses', *Quarterly Journal of Economics* 117(3), 1039-1073.

Smith, J. B. & Stelcner, M. (1985), 'Labour Supply of Married Women in Canada, 1980', *Working Paper* 1985-7, *Department of Economics, Concordia University, Montreal, Quebec.*

Stern, N. (1986), 'On the Specification of Labor Supply Function', *in* R. Blundell & I. Walker, eds, 'Unemployment, Search and Labour Supply', Cambridge University Press, pp. 121-142.

Wales, T. & Woodland, A. (1979), 'Labour Supply and Progressive Taxes', *The Review of Economic Studies* 46(1), 83-95.

Wooldridge, J. M. (2001), *Econometric Analysis of Cross Section and Panel Data*, The MIT Press.

Van Soest, A. (1995), 'Discrete Choice Models of Family Labor Supply', *Journal of Human Resources* 30(1), 63-88.

A Appendix

A.1 Definitions of the variables

Log Wage: Logarithmic gross hourly wage or logarithmic net effective hourly wage; calculated for known observations from the data set and predicted by the Heckit sample selection model for non-workers whose observations were missing.
Labor force participation (indicator): Defined as a binary variable that takes value one for people over the minimum school-living age of 16, who were working[37] or unemployed[38] in the week before the week of interview person is employed. These persons constitute the labor force. People who are neither working nor unemployed by the International Labor Organization (ILO) measure were coded by zero.
Education: A binary variable that equals one if the terminal education age[39] was at least 16 indicating that an individual finished at least high school.
Other income: Constructed as the sum of net household income (after taxation) of other household members and non-labor income of the individual. Non-labor income of an individual is derived as the sum of rental income, income from investments, alimony or maintainace payments,child and state benefits[40].
Married: A binary variable that equals one for married individuals who are living with their husband or wife, or married individuals who are separated from their husband or wife. This classification applies to persons aged 16 to 59 who answer the marital history questions. Cohabiting people are categorised according to formal marital status[41]. The classification differs from strict legal marital status in accepting the respondents' opinion of whether their marriage

[37] The category of working persons includes individuals aged 16 and over who, in the week before the week of interview, worked for wages, salary or other form of cash payment such as commission or tips, for any number of hours. It covers persons absent from work in the reference week because of holiday, sickness, strike, or temporary lay-off, provided they had a job to return to with the same employer. It also includes persons attending an educational establishment during the specified week if they were paid by their employer while attending it, people on Government training schemes and unpaid family workers. Unfortunately, 153 unpaid family workers were excluded from estimation due to a survey mistake, where those persons were coded as not eligible to answer the questions about their employment status. This mistake was latter on confirmed by the Office of National Statistics upon my request.

[38] The General Household Survey (GHS) uses the International Labour Organisation (ILO) definition of unemployment. This classifies anyone as unemployed if he or she was out of work and had looked for work in the four weeks before interview, or would have but for temporary sickness or injury, and was available to start work in the two weeks after interview. For 352 individuals who were classified as unemeployed by ILO definition of unemployment, I have coded them with zero due to the fact that they did not supply positive amount of working hours.

[39] Individuals that were still in a process of acquiring an education are coded one because the average terminal education age in the sample was 17.

[40] Other income is transformed from weekly basis that is given in the GHS to annual by multiplying the weekly other income by the total number of weeks in a year,that is 52.

[41] In this dichotomy 'married' generally includes cohabiting and 'non- married' covers those who are single, widowed, separated or divorced and not cohabiting.

has terminated in separation rather than applying the criterion of legal separation.
Children 0-4 Years: A binary variable determining whether any children younger than 5 years of age are present in the household.
Children 5-15 Years: A binary variable determining whether any children from 5 to 15 years of age are present in the household.
Age: Age of the individual.
Age^2: A square of age of the individual.
Non-white: A binary variable for ethnic classification where individuals with non-white ethnic background are coded one and zero for white ethnic background. Non-white ethnic backgrounds include: black Caribbean, black African, other black background, Indian, Pakistani, Bangladeshi, other Asian background, Chinese, other ethnic group and people with mixed ethnic background.
Regional indicators: A binary variables that indicate the household residence region defined by the Nomenclature of Territorial Units for Statistics (NUTS) that serve as the administrative subdivisions of countries for statistical purposes. Region Greater London (encompassing inner and outer London) is set as the base[42].

[42] The first level NUTS regions for UK excluded for some unknown reason Northern Ireland from the survey

B Appendix

B.1 Predicting wages from the Heckman sample selection model

Heckman (1979) showed a persistence of bias in estimation based on non-randomly selected samples. Estimating the wage equation by standard OLS regression is biased when there are unobservables in behaviour between workers and non-workers and when the unobserved characteristic of the decision to work is correlated to the unobservable characteristic of the wage level. One of the situations is when an individuals are more probably to work have on average higher wage levels.

Using Heckman‘s correction approach, I estimate a wage equation conditioning on the non-random selection into employment. A wage equation and labor force participation equation is formulated as follows:

$$\log GRW_i = \mathbf{X}_i'\boldsymbol{\beta} + e_i \tag{37}$$

$$INLF_i = \mathbf{Z}_i'\boldsymbol{\gamma} + u_i \tag{38}$$

where GRW_i is the gross hourly wage and it is observed only if $INLF_i = 1$, $INLF_i$ denotes a binary variable whether an individual i participate in employment. Determinants of wage and participation in the labor force for each individual i are denoted with vectors $\mathbf{X}_i$ and $\mathbf{Z}_i$, respectively. I assume independance of errors, e_i and u_i , across individuals, joint normal distribution with means equal zero, variances σ_e^2 and σ_u^2 and correlation ρ_{eu}. The wage and employment equations are estimated by the Heckit two step estimation, although the maximum likelihood shows more efficiency. Gross hourly wage is derived from the weekly wage by dividing it with hours worked per week. Table 8 and table 9 presents the estimates of the wage and labor force participation equations. The Heckit two step estimates is used to predict gross hourly wages for every individual in the sample.

Table 8: Heckman two step selection estimation - Men

Variable	**Coefficient**	**(Std. Err.)**
Equation 1 : Logarithmic Gross Hourly Wage		
Age	0.054**	(0.016)
Age^2	-0.001**	(0.000)
Education	0.219**	(0.036)
Non-white	-0.108*	(0.048)
Region North East	-0.359**	(0.063)
Region North West	-0.271**	(0.051)
Region YorksHum	-0.253**	(0.052)
Region East Midl	-0.229**	(0.056)
Region West Midl	-0.239**	(0.056)
Region East Engl	-0.171**	(0.053)
Region South East	-0.135**	(0.052)
Region South West	-0.295**	(0.057)
Region Wales	-0.329**	(0.063)
Region Scotland	-0.309**	(0.055)
Intercept	1.350**	(0.334)
Equation 2 : Selection to employment		
Age	0.176**	(0.016)
Age^2	-0.002**	(0.000)
Education	0.192*	(0.076)
Non-white	-0.471**	(0.090)
Other income	-0.003*	(0.002)
Children 0-4 Years	-0.150*	(0.076)
Children 5-15 Years	-0.076	(0.064)
Married	0.439**	(0.062)
Region North East	-0.190	(0.143)
Region North West	0.037	(0.121)
Region YorksHum	0.005	(0.128)
Region East Midl	0.023	(0.129)
Region West Midl	-0.039	(0.124)
Region East Engl	0.153	(0.123)
Region South East	0.197†	(0.108)
Region South West	0.103	(0.134)
Region Wales	-0.139	(0.150)
Region Scotland	-0.136	(0.124)
Intercept	-1.953**	(0.311)
Equation 3 : Mills lambda		
Lambda	-0.721**	(0.215)
N	4,392	
$\chi^2_{(14)}$	223.647	

Bootstrap standard errors, 500 replications

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 9: Heckman two step selection estimation - Women

Variable	Coefficient	(Std. Err.)
Equation 1 :Logarithm of Gross Hourly Wage		
Age	0.051**	(0.007)
Age^2	-0.001**	(0.000)
Education	0.316**	(0.033)
Non-white	-0.056	(0.041)
Region North East	-0.396**	(0.058)
Region North West	-0.289**	(0.043)
Region YorksHum	-0.262**	(0.045)
Region East Midl	-0.292**	(0.050)
Region West Midl	-0.274**	(0.052)
Region East Engl	-0.222**	(0.043)
Region South East	-0.203**	(0.045)
Region South West	-0.336**	(0.043)
Region Wales	-0.394**	(0.060)
Region Scotland	-0.284**	(0.046)
Intercept	1.171**	(0.151)
Equation 2 : Selection to employment		
Age	0.193**	(0.013)
Age^2	-0.003**	(0.000)
Education	0.344**	(0.057)
Non-white	-0.554**	(0.070)
Other income	-0.001	(0.001)
Children 0-4 Years	-0.947**	(0.049)
Children 5-15 Years	-0.584**	(0.046)
Married	0.014	(0.044)
Region North East	-0.009	(0.114)
Region North West	0.120	(0.084)
Region YorksHum	0.151	(0.096)
Region East Midl	0.150†	(0.091)
Region West Midl	-0.102	(0.088)
Region East Engl	0.020	(0.091)
Region South East	0.045	(0.080)
Region South West	-0.019	(0.088)
Region Wales	0.088	(0.114)
Region Scotland	-0.014	(0.091)
Intercept	-2.382**	(0.250)
Equation 3 : Mills lambda		
Lambda	-0.144*	(0.059)
N	5,400	
$\chi^2_{(14)}$	286.393	

Bootstrap standard errors, 500 replications

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 10: Summary statistics of predicted Log Gross Wage - Men

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Log Grs Wage - Observed	2.444	0.675	-4.685	7.445
Log Grs Wage - Heckit pr.	2.444	0.242	1.312	2.901
Log Grs Wage - Linear pr.	2.583	0.189	1.83	2.974
Number of observations	3,909			

Table 11: Summary statistics of predicted Log Gross Wage - Women

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Log Grs Wage - Observed	2.178	0.642	-5.155	5.561
Log Grs Wage - Heckit pr.	2.178	0.187	1.405	2.589
Log Grs Wage - Linear pr	2.233	0.174	1.563	2.61
Number of observations	3,981			

Table 12: Summary statistics of predicted Gross Wage - Men

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Grs Wage Linear pr.	13.713	32.922	0	1710.526
Grs Wage Heckit pr.	13.779	3.929	1.095	22.979
Grs Wage Heckit cond. pr.	15.247	3.509	3.274	23.772
Number of observations	4,392			

Table 13: Summary statistics of predicted Gross Wage - Women

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Grs Wage Linear pr.	8.045	10.827	0	260
Grs Wage Heckit pr.	8.028	2.748	0.165	15.072
Grs Wage Heckit cond. pr.	10.66	2.042	4.527	16.144
Number of observations	5,400			

B.2 Predicting the participation form the Probit model

This subsection contains the set of estimates for the labor force participation decision of men and women for each wage specification.

Table 14: Probit Estimation - Gross Wages, Men

Variable	Coefficient	Std. Err.
Log Wage	$0.57989^{\dagger}$	0.30400
Age	0.14411^{**}	0.02343
Age^2	-0.00203^{**}	0.00026
Education	0.06076	0.10546
Non-white	-0.45379^{**}	0.08907
Other income	-0.00341^{*}	0.00151
Children 0-4 Years	$-0.15464^{\dagger}$	0.08009
Children 5-15 Years	-0.08214	0.06489
Married	0.44522^{**}	0.06608
Intercept	-2.56087^{**}	0.43625
N	4,392	
Log-likelihood	-1383.68523	
$\chi^2_{(9)}$	273.9185	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Bootstrap errors, 1000 replications

Table 15: Probit Estimation - Gross Wage, Women

Variable	Coefficient	Std. Err.
Log Wage	-0.09258	0.20439
Age	0.19835^{**}	0.01758
Age^2	-0.00265^{**}	0.00021
Education	0.36287^{**}	0.09024
Non-white	-0.56708^{**}	0.06653
Other income	-0.00091	0.00080
Children 0-4 Years	-0.94520^{**}	0.04916
Children 5-15 Years	-0.58506^{**}	0.04684
Married	0.01109	0.04655
Intercept	-2.25100^{**}	0.28488
N	5,400	
Log-likelihood	-2707.2384	
$\chi^2_{(9)}$	763.93412	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Bootstrap errors 1000 replications

Table 16: Probit Estimation - Net Wages, Men

Variable	Coefficient	Std. Err.
Log Wage	0.63591†	0.32649
Age	0.14151**	0.02356
Age^2	-0.00199**	0.00027
Education	0.05347	0.10646
Non-white	-0.46489**	0.09135
Other income	-0.00340*	0.00147
Children 0-4 Years	-0.15460†	0.08365
Children 5-15 Years	-0.08232	0.06672
Married	0.44557**	0.06441
Intercept	-2.43794**	0.39412
N	4,392	
Log-likelihood	-1383.67713	
$\chi^2_{(9)}$	262.95763	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Bootstrap errors 1000 replications

Table 17: Probit Estimation - Net Wages, Women

Variable	Coefficient	Std. Err.
Log Wage	-0.04948	0.24577
Age	0.19596**	0.01824
Age^2	-0.00262**	0.00022
Education	0.34609**	0.08778
Non-white	-0.57174**	0.06488
Other income	-0.00092	0.00085
Children 0-4 Years	-0.94547**	0.05219
Children 5-15	-0.58536**	0.04390
Married	0.01151	0.04567
Intercept	-2.29606**	0.28691
N	5,400	
Log-likelihood	-2707.32277	
$\chi^2_{(9)}$	760.76464	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Bootstrap errors 1000 replications